Repercussion of Covid 19 Upsurge: An Analysis on the Efficaciousness of Autoregressive Models in Volatility and Return Estimation of Bitcoin

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Abstract

Cryptocurrencies, especially Bitcoin, is a hot commodity today. High volatility is a common feature of almost all the cryptocurrencies in the world. A systematic exploration and examination of the volatility of cryptos enables the investor to earn more on their investments. After the outbreak of the COVID-19 pandemic, the crypto market witnessed a highly volatile situation with a huge increase in price. The pandemic also affected the volatility and return of Bitcoin. This research aims to analyse and compare the risk and volatility characteristics of Bitcoin after the outbreak of the COVID-19 pandemic. The study further tests the capacity of several autoregressive models, such as ARMA, GARCH, EGARCH, and TARCH in estimating and evaluating the return and volatility associated with Bitcoin. Identified models were tested and compared with the help of Akaike information criteria (AIC) and Schwarz information criteria (SIC). For this article, the data of daily adjusted closing price of Bitcoin INR (BTC-INR) were collected from Yahoo Finance during the period January, 2017 to December, 2021. We witnessed a huge change in the daily average return of Bitcoin after the COVID-19 outbreak. Also, we identified TARCH (1, 1) as the best model in the ARCH family for evaluating and estimating volatility and ARMA (10, 10) as the best model for predicting the return of Bitcoin.

Keywords: Cryptocurrency; Bitcoin; ARMA; ARCH; GARCH; EGARCH; TARCH; Volatility.

Introduction

Recently, cryptocurrency has emerged as a popular issue, attracting the attention of both academics and investors. Cryptocurrency is a type of digital currency that is based on blockchain technology and may be used as a medium of exchange (Tschorsch & Scheuermann, 2016). In 2008, the mysterious programmer Satoshi Nakamoto developed Bitcoin, the first cryptocurrency in the world (Phillip et al., 2018).

With a growing market capitalization, Bitcoin is considered as a viable investment vehicle by many investors throughout the world (Qarni et al., 2019). Bitcoin

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can also be considered as a speculative asset (Corbet et al., 2018). Over time, cryptocurrencies tend to display similar features and become more distinguishable from other asset classes (Pele et al., n.d.). Bitcoin has the potential to operate as a hedging asset against the stock price swings of all foreign marketplaces studied (Garcia-Jorcano & Benito, 2020). Noisy, non-stationary, and deterministically chaotic in nature, the rates are the key features of all most all the crypto.

Since the start of cryptocurrencies, the COVID-19 outbreak has created the first widespread bear market conditions (Conlon et al., 2020). After the COVID-19 outbreak, the crypto market—especially Bitcoin—experienced high volatility in its price than in the pandemic's pre-period (Yousaf & Ali, 2020). High volatility provides an opportunity for the investors to earn more. Critical evaluation and accurate forecast will enable investors to tackle the price volatility and help to make good return on their investment. This study aims to assess the return and volatility characteristics of Bitcoin INR with the help of a few autoregressive econometric models.

Literature Review

The COVID-19 pandemic has affected the world's financial market and the crypto market is no exception (Ali et al., 2020). Due to rising concerns about COVID-19, global equities market investors migrated from holding risky assets to safe-haven assets, and those who held risky assets faced their worst price drop in the last week of February 2020 since the 2008 financial crisis (Park, 2022). Volatility and volume of Bitcoin are the main attractors for a wide range of attention from investors, businesspersons, and academicians (Urquhart, 2018). Persistence properties of cryptos should be analysed for forecasting their volatility, which will help to attain better profits (Abakah et al., 2020). Chu et al.(2017) emphasised the increased need for quantifying the volatility of cryptocurrencies. During the pre-COVID-19 era, volatility transmission was not substantial for any of the cryptocurrency pairs (Yousaf & Ali, 2020). Another study dealt with the volatility spillover of six major crypto markets and the authors identified that USD and EUR experienced a high volatility spill-over effect (Dong et al., 2020). Bouri et al. (2021) employed an autoregressive realized volatility model (HAR-RV) and forecasted the realized volatility of Bitcoin. Global economic policy uncertainty and economic situations affect the volatility of Bitcoin according to Fang et al. (2019). Qarni et al. (2019) suggested that as Bitcoin's popularity and tradability grew, it would have a significant influence on other U.S. financial markets in the future. Due to the rapid fluctuations in the value of cryptocurrencies, data-driven nonparametric models appear to suffer more in predicting downside tail risks (Liu et al., 2020). COVID-19 seems to have had little effect on herding in cryptocurrency markets. Herding stays dependent on up or down market days in all markets analysed, although it did not appear to become stronger throughout the COVID-19 period (Yarovaya et al., 2021). The decentralised Bitcoin market is more volatile, whereas centralised markets are more tail dependent in terms of returns (Matkovskyy, 2019). Le et al. (2021) identified that the COVID-19 outbreak had changed the spillover pattern of fin-tech and other classes of assets including cryptos. Bitcoin does not possess stabile hedging capacity (Klein et al., 2018). Bitcoin volatility is high in speculative conditions (Lopez-Cabarcos et al., 2021). This has a negative impact on its potential role in portfolios (Baur & Dimpfl, 2021). COVID-19 pandemic-related media news had an impact on the volatility of Bitcoin prices (Zhang et al., 2022). According to

Sebastiao and Godinho (2021), machine learning and data analytics provide strong approaches for investigating the predictability of cryptocurrencies and developing effective trading strategies in these markets, even in the face of adverse market situations. ARCH family models are better at forecasting volatility cryptocurrencies than the Stochastic Volatility (SV) model (Kim et al., 2021). ARMA is an econometric model used to predict the present value of one variable based on its past values (Sifat et al., 2019). From the review of literature, we identified that there is a huge change in the volatility and return characteristics of Bitcoin. No serious studies have been done to test the fitness of the autoregressive model for forecasting and evaluating the return and volatility characteristics of Bitcoin-INR after the outbreak of COVID-19. This study is focussed on testing the efficiency of autoregressive models such as ARMA, ARCH, GARCH, EGARCH, and TARCH for forecasting and evaluating the volatility and return of Bitcoin in terms of INR.

Material and methods

3.1. Data Source

For this article, the data of daily adjusted closing price of Bitcoin INR (BTC-INR) were collected from Yahoo Finance during the period January, 2017 – December, 2021. Therefore, there is a total of 1765 daily observations.

Methodology

Daily Log Return

The daily return prices were calculated from the adjusted closing prices of Bitcoin. The study employed the natural log return method for calculating daily returns (Mahendra et al., 2021). The daily return (R_t) of all selected variables calculate using daily adjusted closing price using natural log.

$$(\ln):\ Rti = Ln\,(P_t/P_{t-1})$$

In this, R_{ti} is the daily return of price index *i*, P_t represents the adjusted closing value of price index at given time *t*, and P_{t-1} is the value of the index at the time t-1.

Augmented Dickey-Fuller (ADF) Stationarity test

Testing the presence of unit root is a preliminary requirement as the study deals with time-series data. Augmented Dickey-Fuller (ADF) test was used for ensuring stationarity of data (John, 2019).

$$y_t = c + \beta t + \alpha y_{t-1} + \phi \Delta Y_{t-1} + e_t$$

Rejection of null hypothesis indicates stationarity of data. The test rejects the null hypothesis when the p-value is less than 0.05 and high negative ADF test statistics (Miglietti et al., 2020).

ARMA Model

To find the most appropriate model for forecasting Bitcoin returns, the static properties of the data were verified graphically, and the unit root test, i.e., ADF (Augmented Dickey-Fuller) test was utilized. The Bitcoin return was estimated using the ordinary least squares (OLS) approach if the series was steady. The Bitcoin return moving pattern turned out to be autoregressive (AR), moving average (MA), or a combination of both (ARMA). The AR (p) model can be written as

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots\cdots + \varphi_p Y_{t-p} + \varepsilon_t$$

The MA (q) model can be written as

$$Y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} - \ldots\ldots\ldots \theta_q \varepsilon_{t-q}$$

The combination of AR (p) and MA (q) model i.e. ARMA (p, q) model is expressed in the following form:

$$Y_t = \theta_0 + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots\cdots + \varphi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots\cdots - \theta_q \varepsilon_{t-q}$$

In this equation given above, Y_t and εt are the actual value and random error at time period t respectively; φi (i = 1, 2, 3,……., p) and θ_j (j = 1, 2, 3,…….., q) are model parameters. The integers p and q are referred to as order of autoregressive and moving average, respectively. Random error term ε_t was assumed to be independently and identically distributed (i.i.d.) with mean zero and constant variance σ^2.

Using backward shift operator, the ARMA (p, q) model can be written in the following form:

$$\varphi(B)Y_t = \theta(B)\varepsilon_t$$

Here, $\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots\cdots\cdots \varphi_p B^p$ and $\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots\cdots + \theta_q B^q$.

ARCH LM TEST

Subsequently, a heteroskedasticity test (ARCH LM) on Bitcoin return was done to find the significance of the ARCH effect. If ARCH effect is present and significant, several ARCH family models such as Autoregressive Conditional Heteroskedasticity (ARCH) model, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model, and Threshold Autoregressive Conditional Heteroskedasticity (TARCH) model can be employed. All these models are purported to possess the capacity to forecast volatility of Bitcoin (Caporale & Zekokh, 2019). The models were compared with the help of Akaike information criteria (AIC) and Schwarz information criteria (SIC) (Naik et al., 2020). The models such as ARCH, GARCH, EGARCH, and TARCH were used as variance models to evaluate and forecast the volatility of Bitcoin return.

The GARCH (1, 1) Model

We started with the simplest, the GARCH (1, 1) model specification:

$$Y_t = X_t'\theta + \epsilon_t$$

$$\sigma_t^2 = \omega + \alpha\epsilon^2_{t-1} + \beta\sigma^2_{t-1}$$

In this case, the given mean equation is represented as a function of exogenous variables with an error term. Since σ_t^2 is the one-period ahead forecast variance based on past information, it is known as conditional variance. The conditional variance equation specified is a function of three terms:

•A constant term: ω

•Volatility-related news from the prior period, as indicated by the lag of the squared residual from the mean equation: (the ARCH term). ϵ^2_{t-1}

•Forecast variance of the previous period: (the GARCH term). σ^2_{t-1}

The Threshold GARCH (TARCH) Model

TARCH or Threshold ARCH and Threshold GARCH were proposed by Zakoian, (1994) and Glosten, et al. (1993). The generalized specification for the conditional variance is given by

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{k=1}^{r} \gamma_k \epsilon_{t-k}^2 \Gamma_{t-k}$$

In this equation, $I_t = 1$ if $\epsilon_t < 0$ and 0 otherwise.

In this model, good news ($\epsilon_{t-i} > 0$) and bad news ($\epsilon_{t-i} < 0$), have differential effects on the conditional variance; good news has an impact of α_i, while bad news has an impact of $\alpha_i + \gamma_i$. If $\gamma_i > 0$, bad news increases volatility and we can conclude that there is a leverage effect for the ith order. If $\gamma_i \neq 0$, the news impact is asymmetric.

It should be noted that the GARCH model is a subset of the TARCH model in which the threshold term is set to zero. To estimate a TARCH model, first describe your GARCH model with the ARCH and GARCH order, then alter the Threshold order to the appropriate value.

The Exponential GARCH (EGARCH) Model

Nelson proposed the EGARCH (Exponential GARCH) model (1991). The conditional variance specification is as follows:

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left|\frac{\epsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \frac{\epsilon_{t-k}}{\sigma_{t-k}}$$

Note that the left-hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and also implies that forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that $\gamma_i < 0$. The impact is asymmetric if $\gamma_i \neq 0$.

Results and Discussion

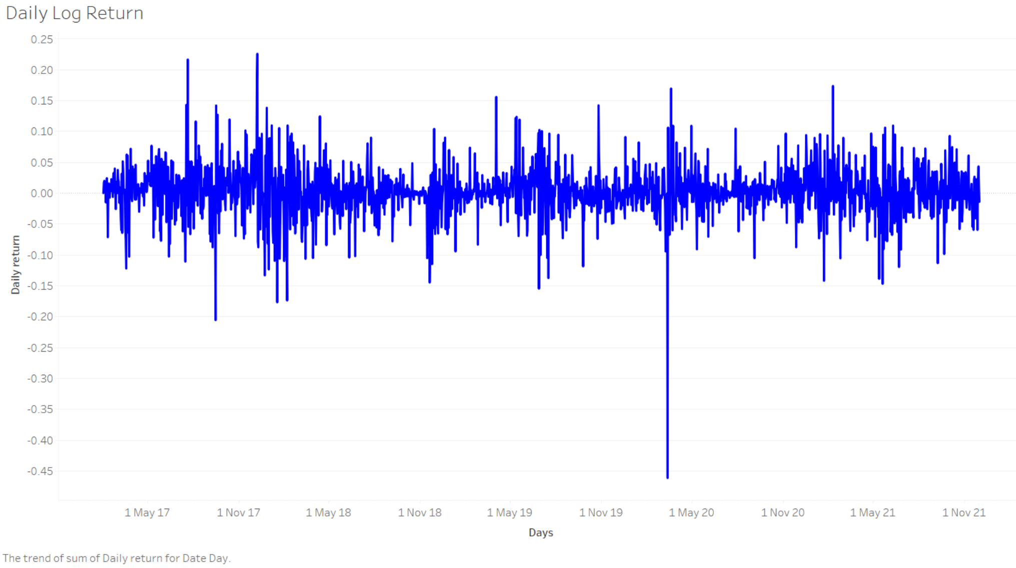
Before modelling the Bitcoin return, we established that the series is stationary. The time series plot and unit root test–Augmented Dickey-Fuller (ADF) determine whether the series is stationary. The time series plot of Bitcoin's adjusted closing price in figure 1 indicates that the series is non-stationary because the mean of the Bitcoin price has changed over time. However, the return series of Bitcoin in figure 2 indicates that the series is stationary because the mean and variance of the Bitcoin return are constant over time.

Figure 1. Time Series Plot of Adjusted Closing Price

Note: Adjusted closing price of Bitcoin from January 2017 to December 2021
Source: Authors' Calculation

The time series plot of Bitcoin adjusted closing price in figure 1 indicates that there is an upward trend in the price, which indicates the presence of unit root.

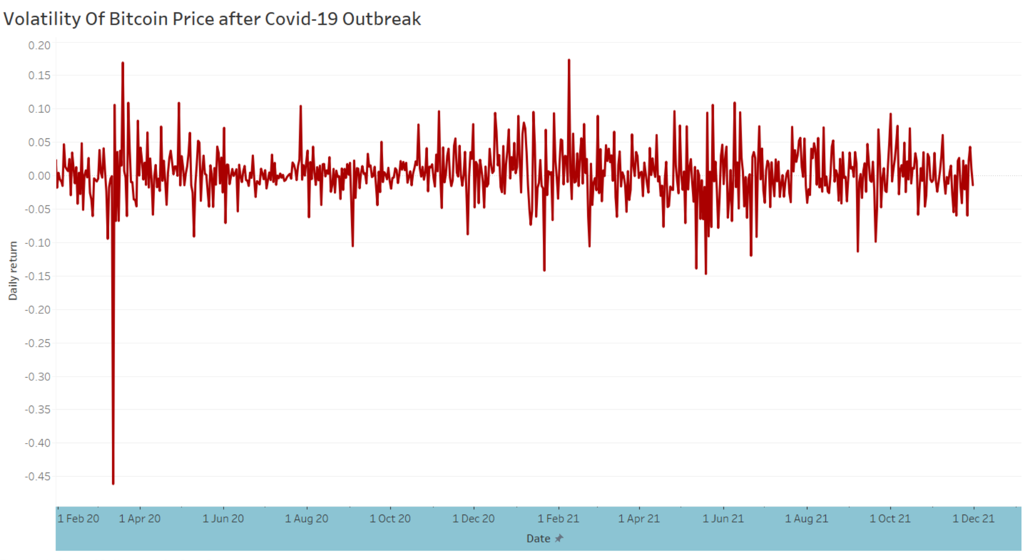
Figure 2. Bitcoin Returns



Note: Daily return of Bitcoin from January 2017 to December 2021 has been plotted.
Source: Authors' calculation.

Figure 2 indicates that there is no presence of trend—either upward or downward. This confirms the stationarity of data. Additionally, we can also identify from the figure that volatility exists in Bitcoin prices.

Figure 3. Volatility in the Price of Bitcoin after COVID-19 Outbreak



Note: Graphical representation of price volatility of Bitcoin from 30th January 2020 to 1st December 2021.
Source: Authors' calculation.

Figure 3 shows the volatility of Bitcoin price after the outbreak of COVID-19. On 30 January 2020, the World Health Organization labelled the outbreak a Public Health Emergency of International Concern, and on 11 March 2020, COVID-19 was declared a pandemic. We can easily trace the effect of the declaration of the pandemic on the price of Bitcoin on the 11th and 12th of March, 2020.

Table 1

Unit Root Test of Bitcoin Return

Unit root test - Augmented Dickey Fuller Test with constant and linear trend					
VARIABLE	P-VALUE	ADF TEST STATISTICS	1% SIGNIFICANCE LEVEL	5% SIGNIFICANCE LEVEL	10% SIGNIFICANCE LEVEL
BITCOIN	0.00	-43.32	-3.43	-2.86	-2.57

Note Stationarity of return data checked with ADF
Source: Authors' calculation.

We performed the Augmented Dickey-Fuller (ADF) test to confirm the presence of unit root. The test result shows a p-value < 0.05. And we finds a higher negative ADF test statistic than that of 1% significance level, 5% significance level, and 10% significance level. It reveals that there is no presence of stationarity (Karp & Van Vuuren, 2017).

Table 2

Descriptive Statistics – Return and Risk Characteristics

Descriptive statistics of Bitcoin return	Last five years	Two year pre-period of COVID-19 outbreak	After COVID-19 outbreak
Mean	0.325345	0.040332	0.362505
Median	0.199301	0.093167	0.231066
Std. Dev.	4.188108	3.891386	4.044034
Skewness	-0.046533	0.047879	-0.88562
Kurtosis	9.622378	5.806729	15.11557
Jarque-Bera	3225.872	249.4231	4191.632
Probability	0	0	0
Observations	1765	759	671

Source : Authors calculation

Table 2 reports the mean and standard deviation that represent the daily average return and risk of Bitcoin. The mean values in the table indicate that there is a huge increase in the daily average return of Bitcoin after the COVID-19 outbreak with minimal change in standard deviation. The Kurtosis value exhibits a Leptokurtic (peaked curve). The Leptokurtic value shows high volatility. The skewness and kurtosis values do not follow the properties of a normal distribution.

From the results of the Jarque-Bera test, it is clear that the data is not normally distributed, since the data sets have a high Jarque-Bera coefficient and a low p-value of 0.05, indicating non-normality (Sahoo, 2021). We had made certain that the tools and procedures we employed were not sensitive to data normality.

Figure 4. Correlogram of Bitcoin Return

	AC	PAC	Q-Stat	Prob
1	-0.032	-0.032	1.7554	0.185
2	0.042	0.041	4.8037	0.091
3	-0.003	-0.001	4.8228	0.185
4	0.015	0.013	5.1975	0.268
5	0.027	0.028	6.4710	0.263
6	0.037	0.037	8.8653	0.181
7	-0.035	-0.035	11.064	0.136
8	-0.007	-0.012	11.143	0.194
9	-0.008	-0.007	11.261	0.258
10	0.069	0.068	19.806	0.031
11	0.004	0.008	19.833	0.048
12	0.000	-0.004	19.833	0.070
13	-0.005	-0.002	19.872	0.098
14	0.019	0.018	20.525	0.114
15	0.003	-0.000	20.539	0.152
16	-0.002	-0.009	20.544	0.197
17	0.049	0.053	24.784	0.100
18	-0.011	-0.006	25.000	0.125
19	0.039	0.035	27.742	0.089
20	0.043	0.041	31.084	0.054

Note: It used for fixing lag value of ARMA model.
Source: Authors' calculation

For fitting an ARMA model it is necessary to determine the number of AR or MA terms. Thus, the ACF and PACF plots of the Bitcoin return series provides information regarding the sequence of AR and MA terms necessary to fit a model (Bakar & Rosbi, 2017). The sample ACF from the series (figure 4) reveals that the most dominant spike at lag 10 is statistically significant for both ACF and PACF. We chose ARMA (10, 10) as the best model to anticipate the Bitcoin return among the various ARMA models based on the ACF and PACF plots, and this model was also chosen based on the Correlogram plot.

Table 3

ARMA Estimation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001807	0.000834	2.16628	0.0304
DAILY_ RETURN(10)	0.25513	0.015367	16.6021	0
MA(10)	-0.182381	0.016148	-11.295	0
SIGMASQ	0.00177	3.18E-05	55.5807	0

Note: Testing the fitness of the model.
Source: Authors' calculation.

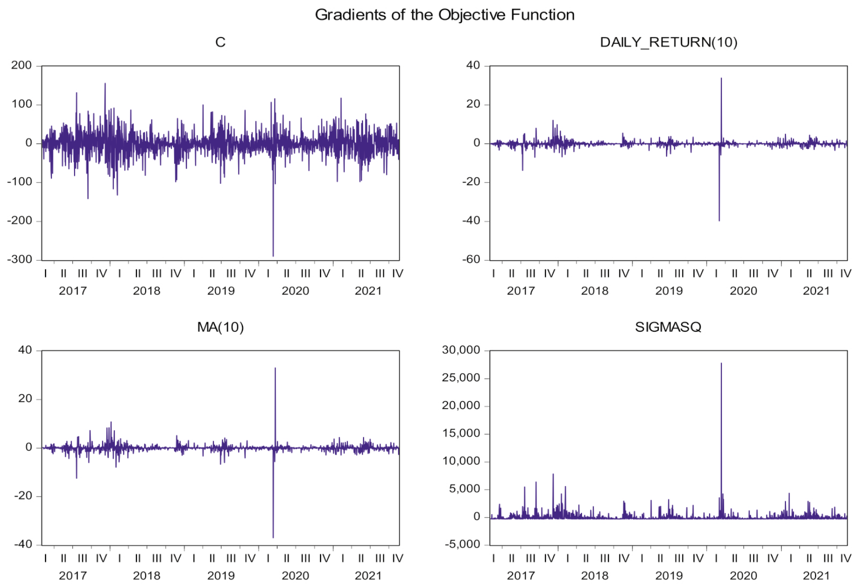
The ARMA model estimation result shows that all the co-efficients are statistically significant as the p-value is less than 0.05 (Bakar & Rosbi, 2017). So we can predict the return of Bitcoin with the help of this model.

Estimation Equation of Bitcoin:

DAILY RETURN = C (1) + C (2)*DAILY_RETURN (10) + [MA (10) =C (3)]

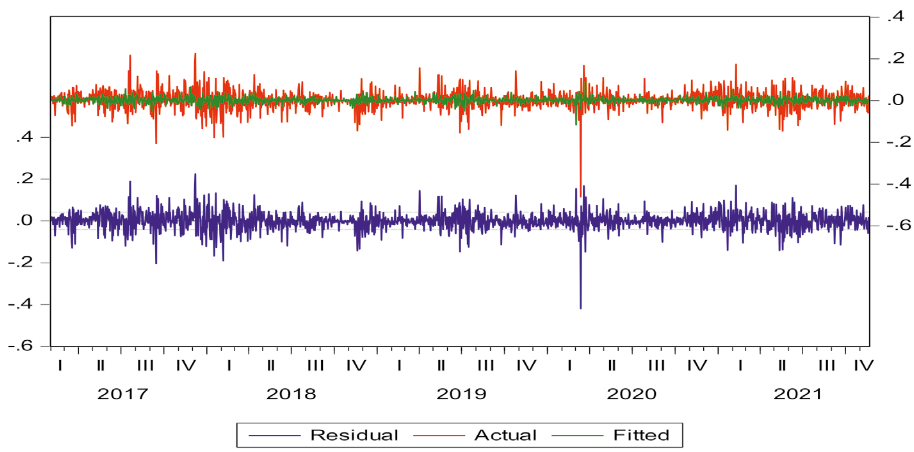
Re= 0.00180689970742 + 0.255127813203*R (t-10) + [MA (10) =-0.182378767556]

Figure 5. Gradient Graph of ARMA (10, 10) model



Note: Each set of coefficient gradients is represented by its own graph. We can use these tools to look for observations with outlier values for the gradients in our data.
Source: Authors' calculation.

Figure 6. Residual Plot of ARMA (10, 10) Model



Note: Plot of residual, actual and fitted value of ARMA (10, 10) model.
Source: Authors' calculation.

We utilised the residual plot in figure 6 and the ARCH LM test to see if the model had an ARCH effect after fitting it (Mia & Rahman, 2019).

Table 4

ARCH LM Test

Heteroskedasticity Test: ARCH			
F-statistic	10.55847	Prob. F(1,1752)	0.0012
Obs*R-squared	10.5072	Prob. Chi-Square(1)	0.0012

Note: Results of the ARCH LM test.
Source: Authors' calculation.

Figure 5 indicates that the volatility has changed over time, which indicates that the series may have an ARCH effect. To examine the existence of the ARCH effect, we employed a heteroskedasticity test = ARCH LM Test. Table 4 confirms the existence of an ARCH effect, as its p-value is < 5%. As the ARCH effect is present, the ARCH family of models can be employed (Mia & Rahman, 2019).

ARCH Family Models Analysis and Comparisons

We constructed several ARCH family models such as GARCH, EGARCH, and TARCH for estimating volatility of Bitcoin Return (Bergsli et al., 2022). We chose one model from the ARCH family to forecast Bitcoin return volatility more accurately based on the Akaike and Schwarz information criteria (AIC and SIC) values (Katsiampa, 2017).

Table 5

Comparisons of Different ARCH Family of Models

Models	Coefficients (Prob.)				AIC	SIC
GARCH (1,1)	9.7E-05	1.1E-01	8.5E-01			
P-Value	0.00	0.00	0.00			
TARCH (1,1)	0.000109	0.073094	0.08051	0.83375	-3.62	-3.60
P-Value	0.00	0.00	0.00	0.00		
EGARCH 1,1)	-0.630886	0.206172	-0.048	0.92392	-3.61	-3.59
P-Value	0.00	0.00	0.00	0.00		

Note: Model comparison.
Source: Authors' calculation.

The GARCH (1, 1) result shows that $\beta_1 = 0.105700$, whereas $\beta_2 = 0.848028$ and the decaying rate of volatility is 0.06 since $\beta_1 + \beta_2 < 1$. In this model, β_2 is greater than β_1, which indicates that the reason for the volatility is persistent even if the market mood is off. The volatility of the return will remain constant for a few days without any reason. Suppose any positive news comes the next trading day, the impact will remain for a few more days without any reason. In this case, the market remained highly volatile after the first wave of COVID-19 pandemic period even when the market was recovering very gradually.

In the TARCH (1, 1) model, ARCH term—the coefficient is positive

(0.073094) and statistically significant. Leverage Effect—the coefficient (0.080508) is positive and statistically significant (indicating the leverage effect). GARCH term—the coefficient (0.833753) is positive and statistically significant. As the GARCH coefficient value is higher than the ARCH coefficient value, we can conclude that the volatility is highly persistent and clustering. As far as the leverage effect is concerned, the coefficient is positive and statistically significant, indicating the leverage effect in the series (meaning: negative news has a higher impact than positive news).

In the EGARCH (1, 1) model, the value—0.630886 (constant) is a long-term average. The ARCH coefficient is positive (0.206172) and significant, indicating the impact of past volatility. Leverage effect: the coefficient is negative (-0.047950) and statistically significant, indicating asymmetric effect (meaning awful news has a higher impact than the good news). GARCH coefficient is positive (0.923922) and significant, indicating the impact of past volatility on current volatility.

According to table 5, TARCH (1, 1) is the best model because it has the lowest AIC and SIC values (Naik et al., 2020). The p-values of all the above models are statically significant since they are less than 0.05. We have selected TARCH (1, 1) as the most suitable model for estimating the volatility of Bitcoin return.

Statistical properties of the selected model—TARCH (1, 1)—are shown in figures 6, 7, and 8, as well as table 6.

Table 6

ARCH LM Test: TARCH (1, 1)

Heteroskedasticity Test: TARCH (1, 1)			
F-statistic	0.000719	Prob. F(1,1762)	0.9786
Obs*R-squared	0.00072	Prob. Chi-Square(1)	0.9786

Note: Heteroskedasticity Test: TARCH (1, 1) to test whether there is any ARCH effect in the proposed model.
Source: Authors' calculation.

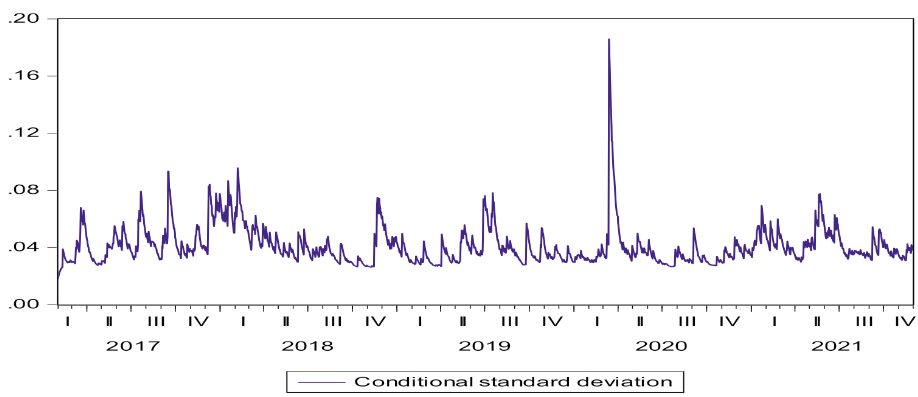
Table 6 indicates the presence of ARCH effect in the model. The p-values stated in the table are above 0.05, which indicates that there is no ARCH effect in the model (Paramanik & Singhal, 2020).

Figure 7. Correlogram of Standardised Residual Squired TARCH (1, 1)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.001	0.001	0.0007	0.979
		2	-0.015	-0.015	0.4044	0.817
		3	-0.022	-0.022	1.2476	0.742
		4	0.032	0.032	3.0655	0.547
		5	0.001	0.000	3.0678	0.690
		6	-0.003	-0.003	3.0869	0.798
		7	0.003	0.005	3.1040	0.875
		8	-0.006	-0.008	3.1770	0.923
		9	-0.016	-0.016	3.6432	0.933
		10	-0.008	-0.007	3.7441	0.958
		11	-0.004	-0.005	3.7694	0.976
		12	-0.005	-0.005	3.8080	0.987
		13	-0.015	-0.014	4.1928	0.989
		14	-0.007	-0.007	4.2816	0.994
		15	0.008	0.008	4.4038	0.996
		16	0.009	0.009	4.5629	0.998
		17	-0.010	-0.009	4.7440	0.998
		18	-0.002	-0.001	4.7491	0.999
		19	-0.014	-0.015	5.0886	0.999
		20	-0.011	-0.012	5.2947	1.000

Note: Indicates AC and PAC of the selected model.
Source: Authors' calculation.

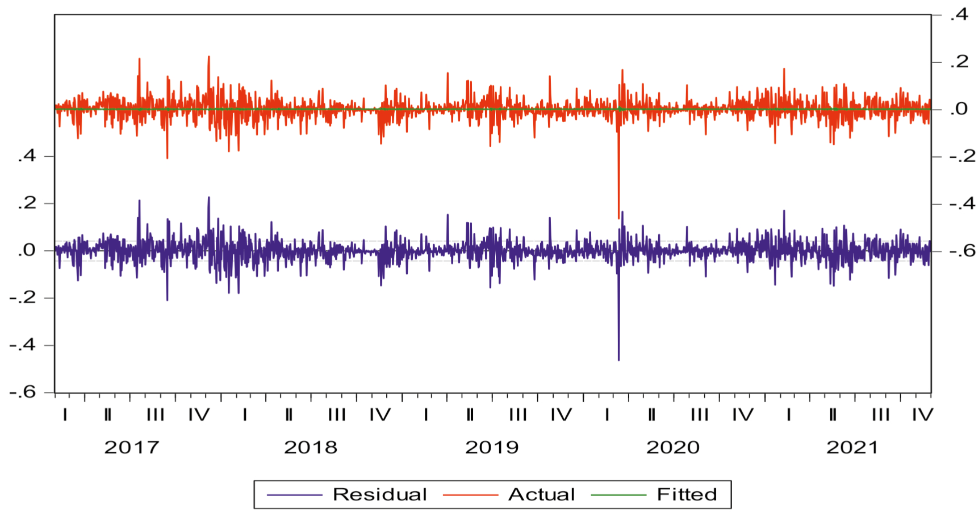
Figure 8. TARCH (1, 1) Conditional Standard deviation



Note: Conditional standard deviation of the selected TARCH (1, 1) model (Karanasos et al., 2004).
Source: Authors' calculation.

Figure 8 shows the conditional standard deviation of the selected TARCH (1, 1) model. It is clear in the figure that high conditional standard deviation is witnessed only in the time of high volatility. Specifically, at the time of the declaration of the COVID-19 pandemic (March 11th and 12th, 2020).

Figure 9. Residual Plot of TARCH (1, 1)



Note: Graphical plot of residual—actual and fitted series—are identical.
Source: Authors' calculation.

Conclusion and Policy Implication

Conclusion

The study arrived at the conclusion that after the outbreak of the COVID-19 pandemic, the price, return, and volatility of Bitcoin have increased. We have developed several models to estimate the return and volatility of Bitcoin in this paper. After determining that the series is stationary using the graphical approach and the unit root test, we chose ARMA (10, 10) as the mean model for return estimation in this investigation. Thereafter, this study attempted to model Bitcoin price volatility using the GARCH, EGARCH, and TARCH models. TARCH (1, 1) is considered the best model in the ARCH family since it has the lowest AIC and SIC values compared to other models. Finally, the study indicates that models such as ARMA (10, 10) and TARCH (1, 1) can accurately forecast and evaluate Bitcoin return and volatility. Also, the evaluation of volatility through the ARCH family indicates that there is a persistence in the volatility even after the outbreak of the COVID-19 pandemic. Future studies can be done to explore the rest of the ARCH family models, and the volatility of the overall crypto market and other cryptocurrencies can be studied.

Policy Implications

Cryptocurrency, especially Bitcoin, is rapidly gaining attention from investors, academicians, and governments. The high degree of price volatility attracts both investors and speculators towards this trading avenue. The models identified through the study can be helpful in understanding the risk in connection with investments in Bitcoin. They further help to predict the return and volatility pattern of Bitcoin, whereby investors can explore the market to earn more. The policymakers can easily trace the pattern of price volatility by employing the identified models. Moreover, by employing these models, they can also easily evaluate the influence of good news and bad news effects on the price volatility of Bitcoin. This will further help in the process of appropriate policy formation.

References

Abakah, E. J. A., Gil-Alana, L. A., Madigu, G., & Romero-Rojo, F. (2020). Volatility persistence in cryptocurrency markets under structural breaks. International Review of Economics and Finance, 69(June), 680–691. https://doi.org/10.1016/j.iref.2020.06.035

Ali, M., Alam, N., & Rizvi, S. A. R. (2020). Coronavirus(COVID-19)-An epidemic or pandemic for financial markets. JOURNAL OF BEHAVIORAL AND EXPERIMENTAL FINANCE, 27. https://doi.org/10.1016/j.jbef.2020.100341 WE - Social Science Citation Index (SSCI)

Bakar, N. A., & Rosbi, S. (2017). Autoregressive Integrated Moving Average (ARIMA) Model for Forecasting Cryptocurrency Exchange Rate in High Volatility Environment: A New Insight of Bitcoin Transaction. International Journal of Advanced Engineering Research and Science, 4(11), 130–137. https://doi.org/10.22161/ijaers.4.11.20

Baur, D. G., & Dimpfl, T. (2021). The volatility of Bitcoin and its role as a medium of exchange and a store of value. EMPIRICAL ECONOMICS, 61(5), 2663–2683. https://doi.org/10.1007/s00181-020-01990-5 WE - Social Science Citation Index (SSCI)

Bergsli, L. O., Lind, A. F., Molnar, P., & Polasik, M. (2022). Forecasting volatility of Bitcoin. RESEARCH IN INTERNATIONAL BUSINESS AND FINANCE, 59. https://doi.org/10.1016/j.ribaf.2021.101540 WE - Social Science Citation Index (SSCI)

Bouri, E., Gkillas, K., Gupta, R., & Pierdzioch, C. (2021). Forecasting Realized Volatility of Bitcoin: The Role of the Trade War. COMPUTATIONAL ECONOMICS, 57(1), 29–53. https://doi.org/10.1007/s10614-020-10022-4 WE - Science Citation Index Expanded (SCI-EXPANDED) WE - Social Science Citation Index (SSCI)

Caporale, G. M., & Zekokh, T. (2019). Modelling volatility of cryptocurrencies using Markov-Switching GARCH models. RESEARCH IN INTERNATIONAL BUSINESS AND FINANCE, 48, 143–155. https://doi.org/10.1016/j.ribaf.2018.12.009 WE - Social Science Citation Index (SSCI)

Chu, J., Chan, S., Nadarajah, S., & Osterrieder, J. (2017). GARCH Modelling of Cryptocurrencies. Journal of Risk and Financial Management, 10(4), 17. https://doi.org/10.3390/jrfm10040017

Conlon, T., Corbet, S., & Mcgee, R. J. (2020). Are cryptocurrencies a safe haven for equity markets? An international perspective from the COVID-19 pandemic. RESEARCH IN INTERNATIONAL BUSINESS AND FINANCE, 54. https://doi.org/10.1016/j.ribaf.2020.101248

Corbet, S., Lucey, B., Peat, M., & Vigne, S. (2018). Bitcoin Futures-What use are they? ECONOMICS LETTERS, 172, 23–27. https://doi.org/10.1016/j.econlet.2018.07.031 WE - Social Science Citation Index (SSCI)

Dong, H., Chen, L., Zhang, X., Failler, P., & Xu, S. (2020). The Asymmetric Effect of Volatility Spillover in Global Virtual Financial Asset Markets: The Case of Bitcoin. Emerging Markets Finance and Trade, 56(6), 1293–1311. https://doi.org/10.1080/1540496X.2019.1671819

Fang, L. B., Bouri, E., Gupta, R., & Roubaud, D. (2019). Does global economic uncertainty matter for the volatility and hedging effectiveness of

Bitcoin? INTERNATIONAL REVIEW OF FINANCIAL ANALYSIS, 61, 29–36. https://doi.org/10.1016/j.irfa.2018.12.010 WE - Social Science Citation Index (SSCI)

Garcia-Jorcano, L., & Benito, S. (2020). Studying the properties of the Bitcoin as a diversifying and hedging asset through a copula analysis: Constant and time-varying. RESEARCH IN INTERNATIONAL BUSINESS AND FINANCE, 54. https://doi.org/10.1016/j.ribaf.2020.101300 WE - Social Science Citation Index (SSCI)

John, E. I. (2019). Effect of Macroeconomic Variables on Stock Market Performance in Nigeria. Journal of Economics, Management and Trade, 2016, 1–14. https://doi.org/10.9734/jemt/2019/v22i630110

Karanasos, M., Karanassou, M., Mary, Q., & Fountas, S. (2004). Analyzing US In fl ation by a GARCH Model with Simultaneous Feedback. January.

Karp, A., & Van Vuuren, G. (2017). The Capital Asset Pricing Model And Fama-French Three Factor Model In An Emerging Market Environment. International Business & Economics Research Journal (IBER), 16(4), 231–256. https://doi.org/10.19030/iber.v16i4.10040

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. ECONOMICS LETTERS, 158, 3–6. https://doi.org/10.1016/j.econlet.2017.06.023

Kim, J. M., Jun, C., & Lee, J. (2021). Forecasting the Volatility of the Cryptocurrency Market by GARCH and Stochastic Volatility. MATHEMATICS, 9(14). https://doi.org/10.3390/math9141614 WE - Science Citation Index Expanded (SCI-EXPANDED) WE - Social Science Citation Index (SSCI)

Klein, T., Thu, H. P., & Walther, T. (2018). Bitcoin is not the New Gold - A comparison of volatility, correlation, and portfolio performance. International Review Of Financial Analysis, 59, 105–116. https://doi.org/10.1016/j.irfa.2018.07.010

Le, L. T., Yarovaya, L., & Nasir, M. A. (2021). Did COVID-19 change spillover patterns between Fintech and other asset classes? RESEARCH IN INTERNATIONAL BUSINESS AND FINANCE, 58. https://doi.org/10.1016/j.ribaf.2021.101441 WE - Social Science Citation Index (SSCI)

Liu, W., Semeyutin, A., Lau, C. K. M., & Gozgor, G. (2020). Forecasting Value-at-Risk of Cryptocurrencies with RiskMetrics type models. RESEARCH IN INTERNATIONAL BUSINESS AND FINANCE, 54. https://doi.org/10.1016/j.ribaf.2020.101259 WE - Social Science Citation Index (SSCI)

Lopez-Cabarcos, M. A., Perez-Pico, A. M., Pineiro-Chousa, J., & Sevic, A. (2021). Bitcoin volatility, stock market and investor sentiment. Are they connected? FINANCE RESEARCH LETTERS, 38. https://doi.org/10.1016/j.frl.2019.101399

Mahendra, A., Mohanty, S. P., & Sudalaimuthu, S. (2021). Financial Astrology and Behavioral Bias: Evidence from India. Asia-Pacific Financial Markets, 28(1), 3–17. https://doi.org/10.1007/s10690-020-09310-8

Matkovskyy, R. (2019). Centralized and decentralized bitcoin markets: Euro vs USD vs GBP. QUARTERLY REVIEW OF ECONOMICS AND FINANCE, 71, 270–279. https://doi.org/10.1016/j.qref.2018.09.005

Mia, S., & Rahman, S. (2019). Evaluating the Forecast Accuracy of Exchange Rate Volatility in Bangladesh Using

ARCH Family of Models. 9(5), 183–190. https://doi.org/10.5923/j.ajms.20190905.01

Miglietti, C., Kubosova, Z., & Skulanova, N. (2020). Bitcoin, Litecoin, and the Euro: an annualized volatility analysis. Studies in Economics and Finance, 37(2), 229–242. https://doi.org/10.1108/SEF-02-2019-0050

Naik, N., Mohan, B. R., & Jha, R. A. (2020). GARCH-Model Identification based on Performance of Information Criteria. Procedia Computer Science, 171, 1935–1942. https://doi.org/10.1016/j.procs.2020.04.207

Paramanik, R. N., & Singhal, V. (2020). Sentiment analysis of Indian stock market volatility. Procedia Computer Science, 176, 330–338. https://doi.org/10.1016/j.procs.2020.08.035

Park, B. J. (2022). The COVID-19 pandemic, volatility, and trading behavior in the bitcoin futures market. Research in International Business and Finance, 59(July 2020), 101519. https://doi.org/10.1016/j.ribaf.2021.101519

Pele, D. T., Wesselhofft, N., Hardle, W. K., Kolossiatis, M., & Yatracos, Y. G. (n.d.). Are cryptos becoming alternative assets? EUROPEAN JOURNAL OF FINANCE. https://doi.org/10.1080/1351847X.2021.1960403 WE - Social Science Citation Index (SSCI)

Phillip, A., Chan, J. S. K., & Peiris, S. (2018). A new look at Cryptocurrencies. ECONOMICS LETTERS, 163, 6–9. https://doi.org/10.1016/j.econlet.2017.11.020

Qarni, M. O., Gulzar, S., Fatima, S. T., Khan, M. J., & Shafi, K. (2019). Inter-markets volatility spillover in u.S. bitcoin and financial markets. Journal of Business Economics and Management, 20(4), 694–714. https://doi.org/10.3846/jbem.2019.8316

Sahoo, M. (2021). COVID-19 impact on stock market: Evidence from the Indian stock market. Journal of Public Affairs, January. https://doi.org/10.1002/pa.2621

Sebastiao, H., & Godinho, P. (2021). Forecasting and trading cryptocurrencies with machine learning under changing market conditions. FINANCIAL INNOVATION, 7(1). https://doi.org/10.1186/s40854-020-00217-x WE - Social Science Citation Index (SSCI)

Sifat, I. M., Mohamad, A., & Shariff, M. S. B. (2019). Lead-Lag relationship between Bitcoin and Ethereum: Evidence from hourly and daily data. RESEARCH IN INTERNATIONAL BUSINESS AND FINANCE, 50, 306–321. https://doi.org/10.1016/j.ribaf.2019.06.012

Tschorsch, F., & Scheuermann, B. (2016). Bitcoin and beyond: A technical survey on decentralized digital currencies. IEEE Communications Surveys and Tutorials, 18(3), 2084–2123. https://doi.org/10.1109/COMST.2016.2535718

Urquhart, A. (2018). What causes the attention of Bitcoin? ECONOMICS LETTERS, 166, 40–44. https://doi.org/10.1016/j.econlet.2018.02.017 WE - Social Science Citation Index (SSCI)

Yarovaya, L., Matkovskyy, R., & Jalan, A. (2021). The effects of a “black swan” event (COVID-19) on herding behavior in cryptocurrency markets. Journal Of International Financial Markets Institutions & Money, 75. https://doi.org/10.1016/j.intfin.2021.101321 WE - Social Science Citation Index (SSCI)

Yousaf, I., & Ali, S. (2020). The COVID-19 outbreak and high frequency information transmission between major cryptocurrencies: Evidence from the VAR-DCC-GARCH approach. BORSA ISTANBUL REVIEW, 20, S1–S10. https://doi.org/10.1016/j.bir.2020.10.003 WE - Social Science Citation Index (SSCI)

Zakoian, J.-M. (1994). Threshold heteroskedastic models. Journal of Economic Dynamics and Control, 18(5), 931–955. https://doi.org/ https://doi.org/10.1016/0165-1889(94)90039-6

Zhang, H. W., Hong, H. J., Guo, Y. Q., & Yang, C. (2022). Information spillover effects from media coverage to the crude oil, gold, and Bitcoin markets during the COVID-19 pandemic: Evidence from the time and frequency domains. International Review of Economics & Finance, 78, 267–285. https://doi.org/10.1016/j.iref.2021.12.005 WE - Social Science Citation Index (SSCI)